MRI-BASED CLASSIFICATION OF BRAIN TUMOR TYPE USING SVM

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Abstract— The objective of this study is to investigate the use of pattern classification methods for distinguishing different types of brain tumors, such as tumor malignant , and also for tumor benign. A computer-assisted classification method combining conventional magnetic resonance imaging (MRI) and perfusion MRI is developed and used for differential diagnosis. The proposed scheme consists of several steps including ROI definition, feature extraction, feature selection and classification. The extracted features include grey-level co-occurrence matrix (GLCM) and the other extraction is based on grey-level run-length matrix (GLRLM) Features subset selection is performed using Support Vector machines (SVMs) with recursive feature elimination. The binary SVM classification accuracy, sensitivity, and specificity, assessed by leave-one-out cross-validation on 157 brain tumors using the data base of MICCAI-brats 2014 (The Cancer Imaging Archive (TCIA)).

Keywords — classification, brain tumor, MRI, SVM, feature selection, texture.

I. INTRODUCTION

Brain tumor is one of the major causes of death among people. It is evidence that the chances of survival can be increased if the tumor is detected correctly at its early stage. Detection of these tumors from brain is very difficult at the regions where a tumor is overlapped with dense brain tissues. Visually detection of these abnormal tissues may result in misdiagnosis of volume and location of unwanted tissues due to human errors caused by visual fatigue. Nowadays, automatic brain tumor detection in MRI images is very important in many diagnostic and therapeutic applications. The complex brain tumors can be separated into two categories depending on tumor origin as primary and metastatic tumors. Primary brain tumors are tumors that arise from cells in the brain or from the covering of the brain. A secondary or metastatic brain tumor occurs when cancer cells spread to the brain from a primary cancer in another part of the body. Magnetic Resonance Images are examined by radiologists based on visual interpretation of the films to identify the presence of anomalies . The shortage of radiologists and the large volume of MRI to be analyzed make such readings labor intensive, cost expensive and often inaccurate. The sensitivity of the human eye in interpreting large numbers of images decreases with increasing number of cases, particularly when only a small number of image are affected. Hence there is a need for automated systems for analysis and classification of such medical images . Texture analysis refers to the branch of imaging science that is concerned with the description of characteristic image properties by textual features. However, there is no universally agreed-upon definition of what image texture is and in general different researchers use different definitions depending upon the particular area of application [1]. The texture analysis is used successfully to aid in the diagnosis of medical images from different imaging modalities[2] Although she has no formal definition defined in the field of image processing, texture generally refers to the appearance, structure and organization of the objects it contains. Digital images are comprised of pixels, all of identical shape but each have a value characterizing it. The texture concept can be attributed to the distribution, spatial or occurrences, of pixels value. In this case, the texture analysis is thus a technique for evaluating the position and the pixel value and therefore characterized the underlying structures of the objects in the image[3]. The relationship between the texture features measured on a sample of tissue and the degree of severity of a tumor was confirmed by many Studies from[4]

II. METHODOLOGY

The block diagram of our proposed algorithm is shown in Figure 1. As shown in this figure, after the preprocessing step the images are segmented and the tumor is localized isolated objects. The feature extraction and selection step also measures certain properties of tumor. These features are then passed through a classifier that evaluates the presented evidences and makes a decision on the class that each tumor should be assigned to.
III. PREPROCESSING

In our work, we will focus on noise reduction and filtering images. In particular, we were inspired by the work of Atkins [5]. The objective of the operation is to reduce the amplitude of the intensity variations in each region, while keeping the transitions between adjacent regions. After noise filtering, an operation of brain isolation will keep only useful information for the segmentation and eliminate the rest, considered as irrelevant. After this step, the skull and the meninges and also a number of artifacts will be deleted. This phase is necessary to avoid errors in segmentation.

A. Noise reduction by anisotropic filtering (Perona and Malik model)

The principle of the model of Perona and Malik [6] is to vary the smoothing by varying the diffusion coefficient locally, which gives a homogeneous diffusion of the smoothing for a region. This is the anisotropic diffusion. They modify the diffusion equation in order to perform anisotropic diffusion. This change is based on maximum homogenization at a distance from contours and minimal diffusion near the contours.

B. Isolating the brain with mathematical morphology [7]

The proposed method is based on the diagram block in Figure 2. It consists of defining a mask for regions of interest. To do this, we propose the following steps:

IV. SEGMENTATION

A. K-mean clustering and labeling

This first stage of segmentation is used to automate the detection of the tumor, a vector quantization algorithm K-means (clustering in English) is then used. K-means [11] is an alternating minimization algorithm that given an integer K, will try to separate a set of points using K clusters. In order to detect and label the tumor, we make a classification in five (or six) classes [Khotanlou et al., 2005]: the cerebrospinal fluid (CSF), gray matter (GM), white matter (MB), the tumor (and edema) and background. Since tumor pathologies we treat have a hyper-intensity, they wear, after classification, the highest label. Thereafter, morphological operations are applied to the resulting image to correct any errors in classification (opening and selection of related components).

B. Level-set:

We use a deformable model-Level set for refines the initial segmentation initially detected by K-means. The geometric model of active contours implements a deforming curve in time and space to achieve the boundaries of an object to be detected in an image I (x, y) [8]. The curve is deformed:

- According to its normal.
- At a rate proportional to its curvature.

Noting C the curve, \( \vec{N} \) the inner normal of the curve and F a velocity term depending of curvature \( \kappa \) the evolution equation is of the form:

\[
\frac{\partial C}{\partial t} = FN
\]  

(1)

![Figure 3. A deforming curve according to its curvature](image)

It is important to maintain during the evolution of the curve the stability in the vicinity of zero [9,10], one must also know that the evolution function of the curve \( \varphi \) must satisfy the condition |\( \nabla \varphi \)|=1; for this, Chunming [9] eliminates the need to reset by proposing the following integral while satisfying the above condition:

\[
P(\varphi) = \int \frac{1}{2} (|\nabla \varphi| - 1)^2 dx dy
\]  

(2)

The following subsection discusses the details of each step.
C. Grey-Level Co-Occurrence Matrix

In a statistical texture analysis, texture features were computed on the basis of statistical distribution of pixel intensity at a given position relative to others in a matrix of image. Depending on the number of pixels or dots in each combination, we have the first-order statistics, second-order statistics or higher-order statistics. Feature extraction based on grey-level co-occurrence matrix (GLCM) is the second-order statistics that can be used to analysing image as a texture (Albregtsen, 1995:1). GLCM (also called gray tone spatial dependency matrix) is a tabulation of the frequencies or how often a combination of pixel brightness values in an image occurs (Hall-Beyer, 2005).

A total of twenty two GLCM features are computed with distance d=1 and four different angles (θ= 0°, 45°, 90° and 135°). Mean, range and variance of these twenty two features are computed and a feature vector of total eighty-eight features is formed. A few among these twenty two GLCM features computed based on references provided in [14], are homogeneity, contrast, energy, sum entropy, difference entropy, inertia, cluster shade, cluster prominence, information measure of correlation, autocorrelation, maximum probability, inverse difference moment, dissimilarity, and inverse difference moment normalized.

D. Gray-Level Run-Length Matrix[15]

Grey-level run-length matrix (GLRLM) is a matrix from which the texture features can be extracted for texture analysis. Texture is understood as a pattern of grey intensity pixel in a particular direction from the reference pixels. Run length is the number of adjacent pixels that have the same grey intensity in a particular direction. Gray-level run-length matrix is a two-dimensional matrix where each element P(I,j/0) is the number of elements j with the intensity i, in the direction 0. For example, Figure 5 below shows a matrix of size 4x4 pixel image with 4 gray levels.

<table>
<thead>
<tr>
<th>Image</th>
<th>GLRLM</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>1 2 3 4</td>
<td>1 2 3 4</td>
</tr>
<tr>
<td>1 3 4 4</td>
<td>4 0 0 0</td>
</tr>
<tr>
<td>3 2 2 2</td>
<td>1 0 1 0</td>
</tr>
<tr>
<td>4 1 4 1</td>
<td>3 0 0 0</td>
</tr>
</tbody>
</table>

Figure 5. The matrix filling example "run length" for a picture 4 × 4 in the direction 0 and four gray levels.

Some texture features can be extracted from the GLRLM matrix. Galloway (Tang, 1998:1602-1609) suggests 5 texture features based on this GLRLM matrix, namely: Shot Runs Emphasis (SRE), Long Runs Emphasis (LRE),
Level Non-uniformity (GLN), Run Length Non-uniformity (RLN), and Run Percentage (RP). Based on the observations that most of the features is only a function of, regardless of the grey level information contained in, Chu et al (1990:415-420) adds 2 more features called Low Gray Level Run Emphasis (LGRE) and High Gray Level Run Emphasis (HGRE). This feature uses grey level of pixels in sequence and is intended to distinguish the texture that has the same value of SRE and LRE but have differences in the distribution of gray levels.asarathy and Holder (Tang, 1998:1602-1609) added 4 more features extracted from the matrix GLRL, namely: Short Run Low Gray-Level Emphasis (SRLGE), Short Run High Gray Level Emphasis (SRHGE), Long Run Low Gray Level Emphasis (LRLGE), and Long Run High Gray Level Emphasis (LRHGE).

Once completed matrix, eleven ratios are calculated [15] in order to construct the characteristic texture vector. The two methods are complementary because one seeks the relationship between the various pixels and the other research the number of pixels possessing the same gray level value in a specified direction.

E. Feature Selection with Cfs Subset Eval

The numbers of texture features extracted from the MR brain image can be irrelevant or redundant. Feature reduction improves classification by searching for the best features subset, from the fixed set of the original features, according to a given processing goal and a feature evaluation criterion: classification accuracy. Hence to reduce the large numbers of features to a smaller set of features in this work we used the algorithm of [M. A. Hall (1998)] correlation-based Feature Subset Selection( Cfs Subset Eval) it Evaluates the worth of a subset of attributes by considering the individual predictive ability of each feature along with the degree of redundancy between them, so that the size of the input matrix (GLCM & GLRLM output) is reduced from 136 to 19. The values of these features are then passed through a classifier that evaluates the presented evidence and makes a decision on the class that each object should be assigned to. Feature extraction and feature dimension reduction are necessary to reduce the input data for a best classification. It is necessary to reduce the dimensionality of the classification task by measuring essential properties or features of the objects.

F. Support Vector Machine Classifier

Support vector machine is a learning method used for classification. In this work a two class SVM classifier is used which finds a hyper plane which separates the data into two classes. A two class SVM contains two classes namely ‘tumor malignant ‘and ‘tumor benign’ as its two outputs. During the training phase the SVM classifier is trained with a training data set which contains feature vectors extracted from the training images and their respective class labels. During the testing phase if an unknown image’s feature vector is given as an input to the trained classifier, it classifies the test image as belonging to one of classes [16]. Experiments are conducted with support vector machine classifier using quadratic kernel function and RBF kernel function.

RESULTS

The results of leave-one-out cross validation using non-linear SVM are shown in Table 1. The feature selection and ranking showed that parameters extracted from perfusion imaging performed well for most classification tasks.

<table>
<thead>
<tr>
<th>Description</th>
<th>Accuracy</th>
<th>Specificity</th>
<th>Sensitivity</th>
</tr>
</thead>
<tbody>
<tr>
<td>All coocurrence matrix</td>
<td>69%</td>
<td>77%</td>
<td>69%</td>
</tr>
<tr>
<td>Coocurrence matrix + Cfs</td>
<td>76%</td>
<td>65%</td>
<td>85%</td>
</tr>
<tr>
<td>All run-length matrix</td>
<td>91%</td>
<td>88%</td>
<td>94%</td>
</tr>
<tr>
<td>run-length matrix +Cfs</td>
<td>92%</td>
<td>89%</td>
<td>95%</td>
</tr>
<tr>
<td>Coocurrence + run-length + Cfs</td>
<td>97%</td>
<td>94%</td>
<td>99%</td>
</tr>
</tbody>
</table>

Figure 7. Plot of Support Vector Machine Classifier
CONCLUSION

In this study we developed a computer-assisted classification method by combining conventional and perfusion MRI for differential tumor diagnosis. We exploited the potential of features extracted automatically from images and investigated the diagnostic value of each feature by applying the support vector machine recursive feature elimination algorithm. The proposed classification scheme achieved high accuracy for most classification problems.

REFERENCES